Copilot Arena: A Platform for Code LLM Evaluation in the Wild

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Motivation

Static benchmarks do not have users in the loop

User studies

operate on a limited, prescribed set of tasks

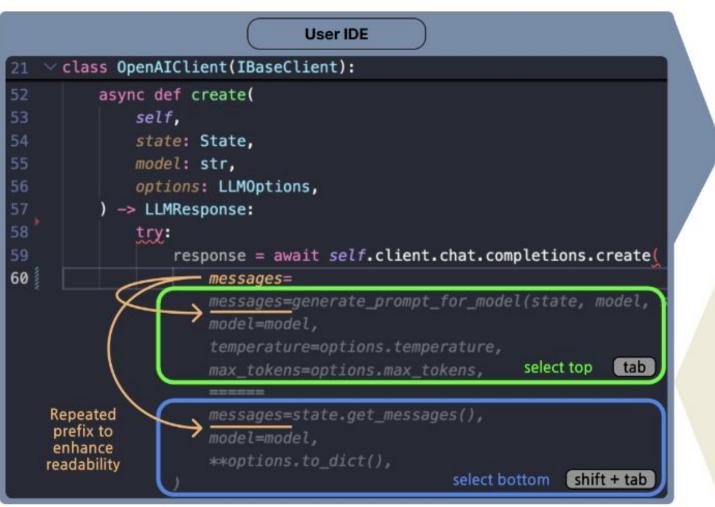
Preference evaluations do not occur in realistic

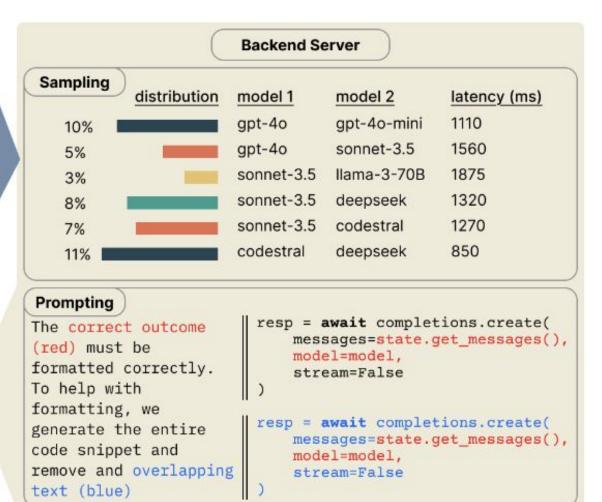
coding envs

Limitations of existing evaluations

System Design

Copilot Arena is a VSCode extension that provides users with pairs of inline code completions from various LLMs. Users provide their votes on which completion is better suited for their task.



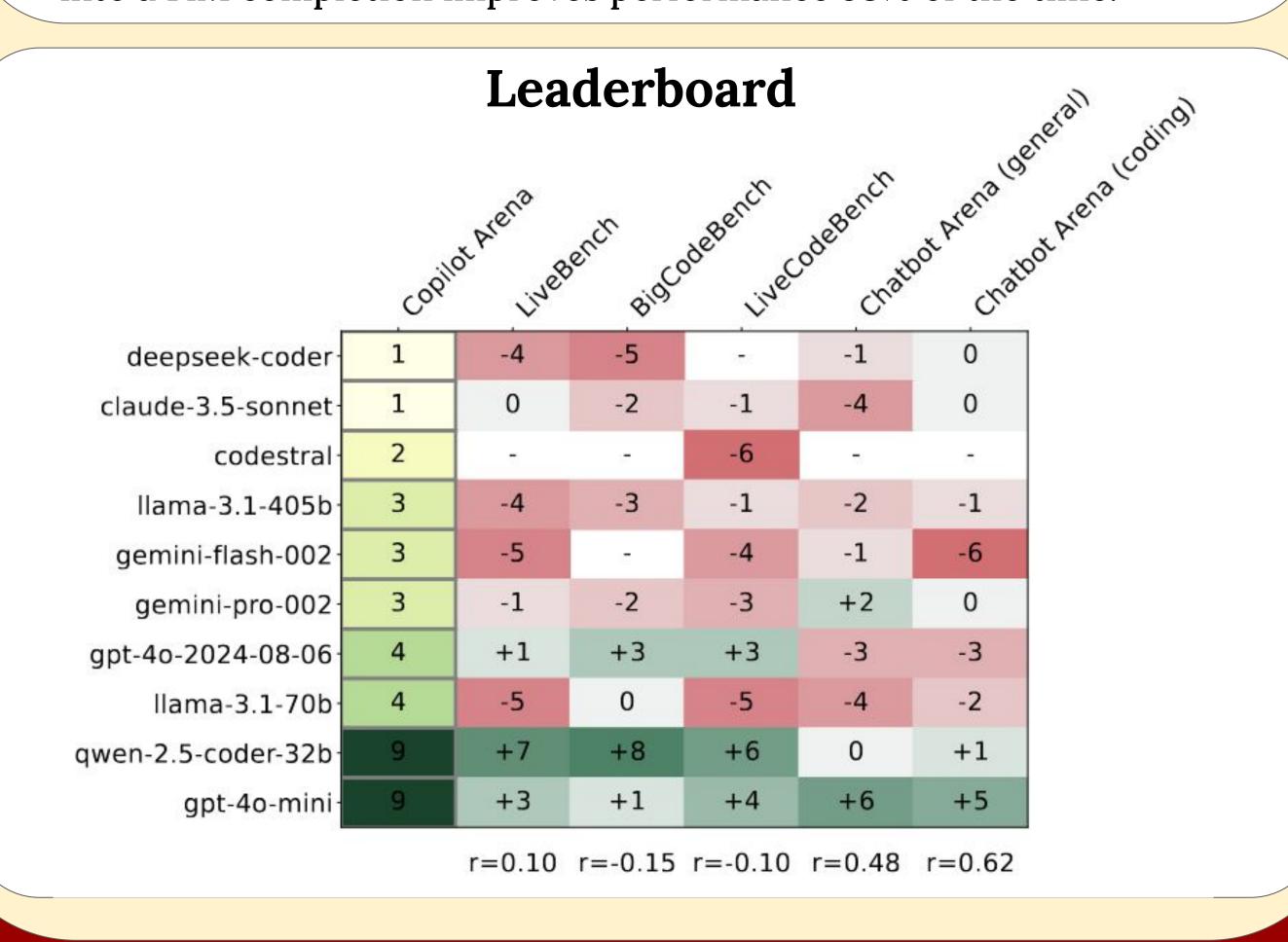


Model Sampling

- We optimize the trade-off between a latency-optimized distribution and a uniform distribution (i.e., to improve coverage).
- This approach decreased median experienced latency by 33%.

Model prompting

- On HumanEval-Infilling, many chat LLMs struggle to "fill in the middle" (FiM).
- Allowing LLMs to generate code snippets and post-processing them into a FiM completion improves performance 93% of the time.



Copilot Arena

has served over 4.5 million suggestions from 10 LLMs and collected over 11k votes.

We find the following key insights:

- 1. Existing evaluations do not necessarily correlate well with in-the-wild preferences.
- 2. Model performance is affected by task, context, and code structure. No model that is "one-size-fits-all."
- 3. Diverse and realistic human preference data is essential for effective code generation models. Smaller models tend to perform better on data similar to static benchmarks.

Full Paper

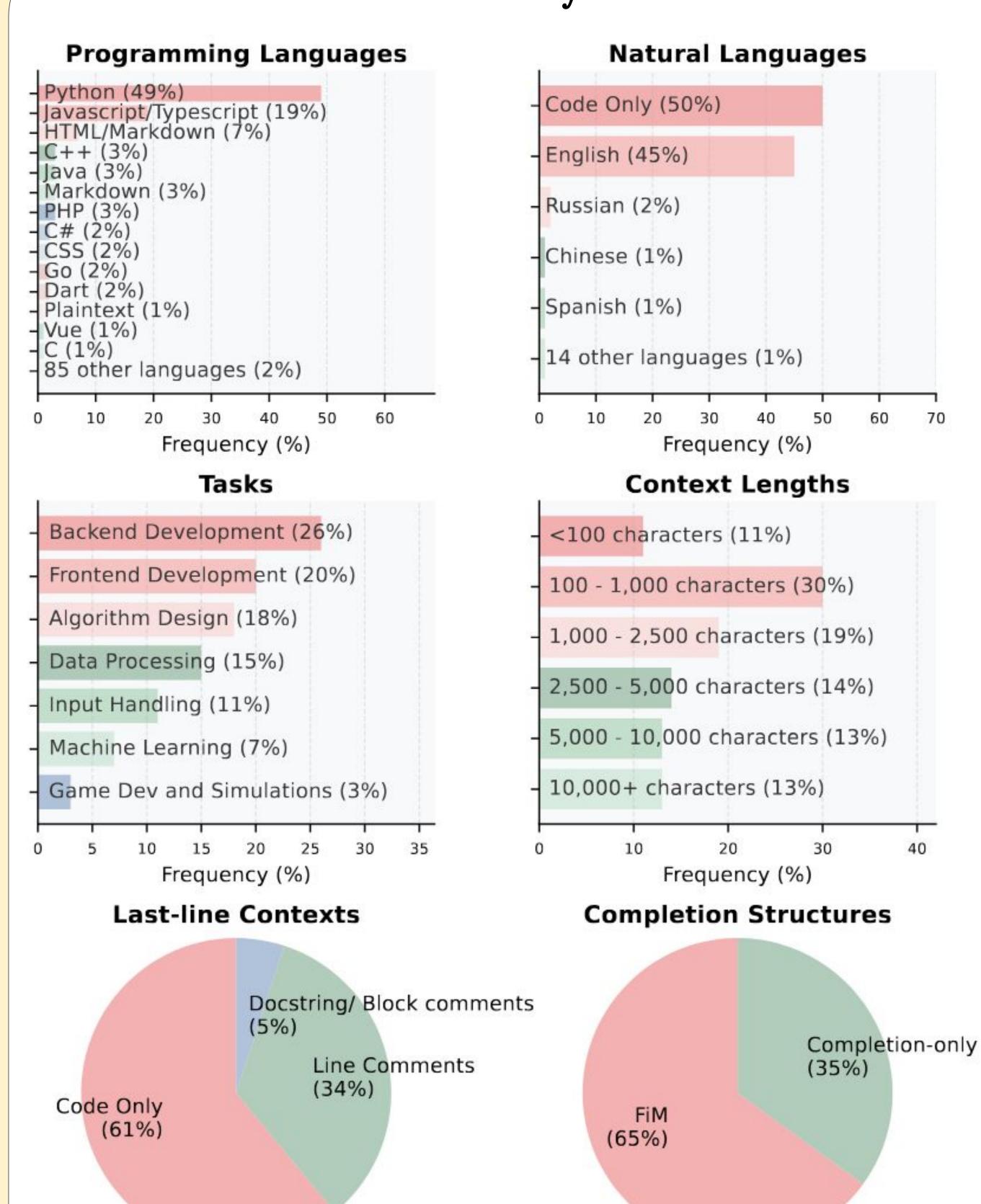


Repository





Data Analysis



Key differentiators in our data:

- 103 programming languages; significantly more than other benchmarks
- Less interview style problems (i.e., algorithm design) and more real-world problems (i.e., backend and frontend development).
- Structurally diverse problems, comprising a mixture of infilling versus code completion and forms of docstring tasks.

Insights into user preferences

We partition each feature into contrasting subsets (e.g. FiM vs non-FiM). We compute a win-rate difference matrix, i.e., the number of substantial differences in the win-rate between each subset:

	Front/Backend	Long Context	FiM	Non-Python
deepseek-coder-	0,-3	+2, 0	+1, 0	0, 0
claude-3.5-sonnet	+4, 0	0,-1	+2, 0	+1, 0
codestral-	+1, 0	+1,-1	0, 0	0, 0
llama-3.1-405b	+1,-4	+1,-1	0, 0	0, 0
gemini-flash-002	+1,-2	0, 0	+1,-2	0, 0
gemini-pro-002	+1, 0	+3, 0	+2, 0	0,-1
jpt-4o-2024-08-06-	+1, 0	0,-2	0,-2	+1, 0
llama-3.1-70b	+4, 0	+1, 0	+1,-2	0, 0
ven-2.5-coder-32b	0,-2	0,-3	0, 0	0,-2
gpt-4o-mini-	+1,-3	Θ, Θ	0,-1	+1, 0
% Total Changes	s: 31.1	17.8	15.6	6.7